UE19CS332-Algorithms of the Intelligent Web and Information Retrieval

Project Title: Anime Recommendation System using Collaboratory based model and content based recommendation model.

Synopsis: This project is a simple anime recommendation system which will recommend 10 anime as per user for the collaboratory model and based on an anime title for the content based model.

Functionality: We will perform data cleaning and preprocessing onto the dataset and then filter out anime with less than fewer ratings and any other relevant filters.
After than we'll make a model and run it through that. Then output a list of 10 anime to the user.

Software Requirements: Google colab, Browser (Google Chrome)

Expected Output: List of 10 anime outputted by the model.

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Collaboratory based model:

Code and output:

```
[1] import io
    import pandas as pd
    import statistics
    import matplotlib.pyplot as plt
    from sklearn.metrics.pairwise import cosine_similarity
    import operator
    from google.colab import files
```

```
[2] from google.colab import drive
    drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
[18] ratings = pd.read_csv('/content/drive/MyDrive/rating.csv')
```

```
# uploaded = files.upload()
anime = pd.read_csv('/content/drive/MyDrive/anime.csv')
```

```
[5] ratings.head()
```

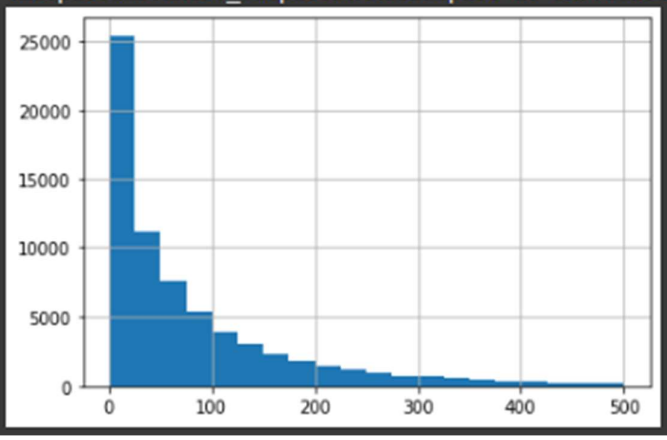
	user_id	anime_id	rating
0	1	20	-1
1	1	24	-1
2	1	79	-1
3	1	226	-1
4	1	241	-1

```
[6] ratings = ratings[ratings.rating != -1]
    ratings.head()
```

	user_id	anime_id	rating
47	1	8074	10
81	1	11617	10
83	1	11757	10
101	1	15451	10
153	2	11771	10

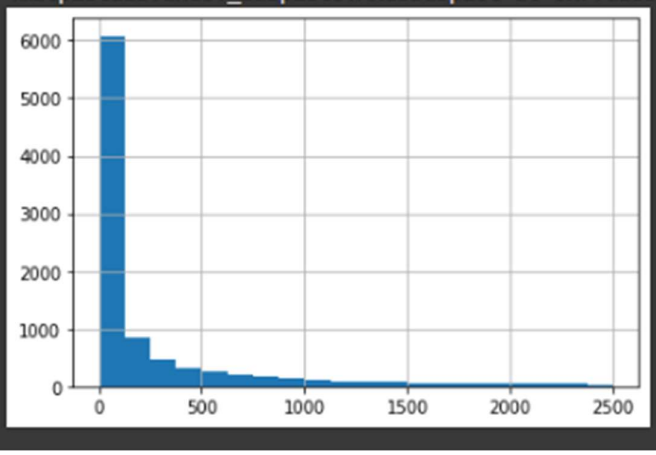
```
[7]  # number of ratings
     print(len(ratings))

     # number of users
     print(len(ratings['user_id'].unique()))

     # number of unique animes (in anime list, not ratings)
     print(len(anime['anime_id'].unique()))

     # avg number of anime rated per user
     ratings_per_user = ratings.groupby('user_id')['rating'].count()
     statistics.mean(ratings_per_user.tolist())

     # distribution of ratings per user
     # (we may want to exclude users without many data points)
     %matplotlib inline
     ratings_per_user.hist(bins=20, range=(0,500))
```

```
6337241
69600
12294
<matplotlib.axes._subplots.AxesSubplot at 0x7fd1b352c5d0>
```



```
[8]  # avg number of ratings given per anime
     ratings_per_anime = ratings.groupby('anime_id')['rating'].count()
     statistics.mean(ratings_per_anime.tolist())

     # distribution of ratings per anime
     %matplotlib inline
     ratings_per_anime.hist(bins=20, range=(0,2500))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd1b33d79d0>
```




```
[9]  # counts of ratings per anime as a df
     ratings_per_anime_df = pd.DataFrame(ratings_per_anime)
     # remove if < 1000 ratings
     filtered_ratings_per_anime_df = ratings_per_anime_df[ratings_per_anime_df.rating >= 1000]
     # build a list of anime_ids to keep
     popular_anime = filtered_ratings_per_anime_df.index.tolist()
```

```
     # counts ratings per user as a df
     ratings_per_user_df = pd.DataFrame(ratings_per_user)
     # remove if < 500
     filtered_ratings_per_user_df = ratings_per_user_df[ratings_per_user_df.rating >= 500]
     # build a list of user_ids to keep
     prolific_users = filtered_ratings_per_user_df.index.tolist()
```

```
[11] filtered_ratings = ratings[ratings.anime_id.isin(popular_anime)]
     filtered_ratings = ratings[ratings.user_id.isin(prolific_users)]
     len(filtered_ratings)
```

```
1005314
```

```
[12] rating_matrix = filtered_ratings.pivot_table(index='user_id', columns='anime_id', values='rating')
     # replace NaN values with 0
     rating_matrix = rating_matrix.fillna(0)
     # display the top few rows
     rating_matrix.head()
```

anime_id	1	5	6	7	8	15	16	17	18	19	...	34238	34239	34240	34252	34283	34324	34325	34349	34367	34475
user_id																					
226	8.0	0.0	8.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
271	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	10.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
294	7.0	7.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
392	7.0	0.0	7.0	0.0	0.0	0.0	0.0	0.0	7.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
446	9.0	8.0	9.0	0.0	0.0	0.0	0.0	0.0	0.0	10.0	...	0.0	0.0	9.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 9591 columns

```
[13] rating_matrix.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1365 entries, 226 to 73502
Columns: 9591 entries, 1 to 34475
dtypes: float64(9591)
memory usage: 99.9 MB
```

```
[14] def similar_users(user_id, matrix, k=3):
        # create a df of just the current user
        user = matrix[matrix.index == user_id]

        # and a df of all other users
        other_users = matrix[matrix.index != user_id]

        # calc cosine similarity between user and each other user
        similarities = cosine_similarity(user,other_users)[0].tolist()

        # create list of indices of these users
        indices = other_users.index.tolist()

        # create key/values pairs of user index and their similarity
        index_similarity = dict(zip(indices, similarities))

        # sort by similarity
        index_similarity_sorted = sorted(index_similarity.items(), key=operator.itemgetter(1))
        index_similarity_sorted.reverse()

        # grab k users off the top
        top_users_similarities = index_similarity_sorted[:k]
        users = [u[0] for u in top_users_similarities]

        return users
```

```
[15] def recommend_item(user_index, similar_user_indices, matrix, items=10):

        # load vectors for similar users
        similar_users = matrix[matrix.index.isin(similar_user_indices)]
        # calc avg ratings across the 3 similar users
        similar_users = similar_users.mean(axis=0)
        # convert to dataframe so its easy to sort and filter
        similar_users_df = pd.DataFrame(similar_users, columns=['mean'])


        # load vector for the current user
        user_df = matrix[matrix.index == user_index]
        # transpose it so its easier to filter
        user_df_transposed = user_df.transpose()
        # rename the column as 'rating'
        user_df_transposed.columns = ['rating']
        # remove any rows without a 0 value. Anime not watched yet
        user_df_transposed = user_df_transposed[user_df_transposed['rating']==0]
        # generate a list of animes the user has not seen
        animes_unseen = user_df_transposed.index.tolist()

        # filter avg ratings of similar users for only anime the current user has not seen
        similar_users_df_filtered = similar_users_df[similar_users_df.index.isin(animes_unseen)]
        # order the dataframe
        similar_users_df_ordered = similar_users_df.sort_values(by=['mean'], ascending=False)
        # grab the top n anime
        top_n_anime = similar_users_df_ordered.head(items)
        top_n_anime_indices = top_n_anime.index.tolist()
        # lookup these anime in the other dataframe to find names
        anime_information = anime[anime['anime_id'].isin(top_n_anime_indices)]

        return anime_information #items
```

```
[16] similar_user_indices = similar_users(271, rating_matrix)
     print(similar_user_indices)
     recommend_item(271, similar_user_indices, rating_matrix)
```

```
[1103, 13652, 20314]
```

	anime_id	name	genre	type	episodes	rating	members
10	4181	Clannad: After Story	Drama, Fantasy, Romance, Slice of Life, Supern...	TV	24	9.06	456749
36	11741	Fate/Zero 2nd Season	Action, Fantasy, Supernatural, Thriller	TV	12	8.73	340973
94	10087	Fate/Zero	Action, Fantasy, Supernatural	TV	13	8.51	453630
96	9756	Mahou Shoujo Madoka★Magica	Drama, Magic, Psychological, Thriller	TV	12	8.51	462974
180	18195	Little Busters!: Refrain	Comedy, Drama, Romance, School, Slice of Life,...	TV	13	8.36	71820
223	2167	Clannad	Comedy, Drama, Romance, School, Slice of Life,...	TV	23	8.30	566690
262	23289	Gekkan Shoujo Nozaki-kun	Comedy, Romance, School	TV	12	8.24	292622
335	12189	Hyouka	Mystery, School, Slice of Life	TV	22	8.17	372246
370	4059	Clannad: Mou Hitotsu no Sekai, Tomoyo-hen	Drama, Romance, School, Slice of Life	Special	1	8.14	160423
504	6351	Clannad: After Story - Mou Hitotsu no Sekai, K...	Drama, Romance, School	Special	1	8.02	138364

```
similar_user_indices = similar_users(226, rating_matrix)
print(similar_user_indices)
recommend_item(226, similar_user_indices, rating_matrix)
```

```
[30773, 39021, 45603]
```

	anime_id	name	genre	type	episodes	rating	members
6	11061	Hunter x Hunter (2011)	Action, Adventure, Shounen, Super Power	TV	148	9.13	425855
16	23273	Shigatsu wa Kimi no Uso	Drama, Music, Romance, School, Shounen	TV	22	8.92	416397
39	12365	Bakuman. 3rd Season	Comedy, Drama, Romance, Shounen	TV	25	8.71	133620
67	22535	Kiseijuu: Sei no Kakuritsu	Action, Drama, Horror, Psychological, Sci-Fi, ...	TV	24	8.59	425457
87	10030	Bakuman. 2nd Season	Comedy, Drama, Romance, Shounen	TV	25	8.53	151561
131	4224	Toradora!	Comedy, Romance, School, Slice of Life	TV	25	8.45	633817
150	57	Beck	Comedy, Drama, Music, Shounen, Slice of Life	TV	26	8.40	148328
184	7674	Bakuman.	Comedy, Romance, Shounen	TV	25	8.35	246899
206	813	Dragon Ball Z	Action, Adventure, Comedy, Fantasy, Martial Ar...	TV	291	8.32	375662
374	17265	Log Horizon	Action, Adventure, Fantasy, Game, Magic, Shounen	TV	25	8.14	387100

Content based model:

Code and output:

```
[1] import numpy as np
    import pandas as pd
    import scipy as sp
    import os
    import matplotlib.pyplot as plt
    from google.colab import files
```

```
[2] from google.colab import drive
    drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
[3] anime = pd.read_csv('/content/drive/MyDrive/anime.csv')
    anime.head()
```

	anime_id	name	genre	type	episodes	rating	members
0	32281	Kimi no Na wa.	Drama, Romance, School, Supernatural	Movie	1	9.37	200630
1	5114	Fullmetal Alchemist: Brotherhood	Action, Adventure, Drama, Fantasy, Magic, Mili...	TV	64	9.26	793665
2	28977	Gintama°	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.25	114262
3	9253	Steins;Gate	Sci-Fi, Thriller	TV	24	9.17	673572
4	9969	Gintama'	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.16	151266

```
[4] rating = pd.read_csv('/content/drive/MyDrive/rating.csv')
    rating.head()
```

	user_id	anime_id	rating
0	1	20	-1
1	1	24	-1
2	1	79	-1
3	1	226	-1
4	1	241	-1

```
[5] anime.shape
```

```
(12294, 7)
```

```
rating.shape
```

```
(7813737, 3)
```

```
[7] missing = anime.loc[(anime['episodes']=="Unknown") & (anime['type'].isnull())]
    missing.shape
```

```
(25, 7)
```

```
[8] anime.isnull().sum()
```

```
anime_id      0
name          0
genre        62
type         25
episodes      0
rating      230
members       0
dtype: int64
```

Treating 'type' and 'genre' column of anime dataset as equal. Therefore using concat & label encoding,the algorithm will not treat a certain category more important than the other categories.

```
[9] anime = pd.concat([anime, anime['type'].str.get_dummies(), anime['genre'].str.get_dummies(sep=',')], axis=1)
    anime.head()
```

	anime_id	name	genre	type	episodes	rating	members	Movie	Music	ONA	...	Shoujo	Shounen	Slice of Life	Space	Sports	Super Power	Supernatural	Thriller	Vampire	Yaoi
0	32281	Kimi no Na wa.	Drama, Romance, School, Supernatural	Movie	1	9.37	200630	1	0	0	...	0	0	0	0	0	0	0	0	0	0
1	5114	Fullmetal Alchemist: Brotherhood	Action, Adventure, Drama, Fantasy, Magic, Mili...	TV	64	9.26	793665	0	0	0	...	0	0	0	0	0	0	0	0	0	0
2	28977	Gintama°	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.25	114262	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	9253	Steins;Gate	Sci-Fi, Thriller	TV	24	9.17	673572	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	9969	Gintama'	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.16	151266	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 95 columns

```
[10] from sklearn.metrics.pairwise import cosine_similarity
```

```
[11] anime_char = anime.loc[:, "Movie":].copy()
     anime_char.head()
```

	Movie	Music	ONA	OVA	Special	TV	Adventure	Cars	Comedy	Dementia	...	Shoujo	Shounen	Slice of Life	Space	Sports	Super Power	Supernatural	Thriller	Vampire	Yaoi
0	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	1	1	0	0	0	...	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	1	0	0	1	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	1	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	1	0	0	1	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 88 columns

```
[12] cos_sim = cosine_similarity(anime_char.values, anime_char.values)
     cos_sim.shape
```

```
(12294, 12294)
```

```
[13] cos_sim
```

```
array([[1.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.31622777],
       [0.        , 1.        , 0.375     , ..., 0.        , 0.        ,
        0.        ],
       [0.        , 0.375     , 1.        , ..., 0.        , 0.        ,
        0.        ],
       ...,
       [0.        , 0.        , 0.        , ..., 1.        , 1.        ,
        0.5       ],
       [0.        , 0.        , 0.        , ..., 1.        , 1.        ,
        0.5       ],
       [0.31622777, 0.        , 0.        , ..., 0.5       , 0.5       ,
        1.        ]])
```

```
[14] anime_index = pd.Series(anime.index, index=anime.name).drop_duplicates()
```

```
def content_recommender(anime_name, similarity=cos_sim):
    index = anime_index[anime_name]

    print('Users also watched:\n')
    sim_score = list(enumerate(cos_sim[index]))
    sim_score = sorted(sim_score, key=lambda x: x[1], reverse=True)
    sim_score = sim_score[0:11]
    anime_i = [i[0] for i in sim_score]

    result = anime[['anime_id','name', 'genre', 'rating']].iloc[anime_i].drop(index)
    return result
```

```
content_recommender("Gintama")
```

```
Users also watched:
```

	anime_id	name	genre	rating
2	28977	Gintama°	Action, Comedy, Historical, Parody, Samurai, S...	9.25
4	9969	Gintama'	Action, Comedy, Historical, Parody, Samurai, S...	9.16
9	15417	Gintama': Enchousen	Action, Comedy, Historical, Parody, Samurai, S...	9.11
10896	34096	Gintama (2017)	Action, Comedy, Historical, Parody, Samurai, S...	NaN
8	15335	Gintama Movie: Kanketsu-hen - Yorozuya yo Eien...	Action, Comedy, Historical, Parody, Samurai, S...	9.10
63	21899	Gintama: Yorinuki Gintama-san on Theater 2D	Action, Comedy, Historical, Parody, Samurai, S...	8.60
65	7472	Gintama Movie: Shinyaku Benizakura-hen	Action, Comedy, Historical, Parody, Samurai, S...	8.59
216	9735	Gintama: Shinyaku Benizakura-hen	Action, Comedy, Historical, Parody, Samurai, S...	8.31
306	25313	Gintama: Jump Festa 2014 Special	Action, Comedy, Historical, Parody, Samurai, S...	8.20
1833	161	Peace Maker Kurogane	Action, Comedy, Historical, Samurai, Shounen	7.43

```
[17] content_recommender("Monster")
```

Users also watched:

	anime_id	name	genre	rating
981	323	Mousou Dairinin	Drama, Mystery, Police, Psychological, Superna...	7.74
6998	32438	Mayoiga	Drama, Horror, Mystery, Psychological	5.80
199	28223	Death Parade	Drama, Game, Mystery, Psychological, Thriller	8.33
669	7193	Aoi Bungaku Series	Drama, Historical, Psychological, Seinen, Thri...	7.90
3806	1243	Night Head Genesis	Drama, Horror, Mystery, Psychological, Superna...	6.88
6009	838	Narutaru: Mukuro Naru Hoshi Tama Taru Ko	Drama, Seinen, Thriller	6.28
53	6114	Rainbow: Nisha Rokubou no Shichinin	Drama, Historical, Seinen, Thriller	8.64
54	31240	Re:Zero kara Hajimeru Isekai Seikatsu	Drama, Fantasy, Psychological, Thriller	8.64
96	9756	Mahou Shoujo Madoka★Magica	Drama, Magic, Psychological, Thriller	8.51
201	3002	Gyakkyou Burai Kaiji: Ultimate Survivor	Game, Psychological, Seinen, Thriller	8.33

```
[18] content_recommender("Death Note")
```

Users also watched:

	anime_id	name	genre	rating
144	1889	Higurashi no Naku Koro ni Kai	Mystery, Psychological, Supernatural, Thriller	8.41
778	2994	Death Note Rewrite	Mystery, Police, Psychological, Supernatural, ...	7.84
833	3713	Jigoku Shoujo Mitsuganae	Mystery, Psychological, Supernatural	7.81
2691	3614	Yakushiji Ryouko no Kaiki Jikenbo	Mystery, Police, Supernatural	7.19
6323	2781	Saint Luminous Jogakuin	Mystery, Psychological, Supernatural	6.17
981	323	Mousou Dairinin	Drama, Mystery, Police, Psychological, Superna...	7.74
49	31043	Boku dake ga Inai Machi	Mystery, Psychological, Seinen, Supernatural	8.65
541	7724	Shiki	Mystery, Supernatural, Thriller, Vampire	7.99
1325	2596	Shinreigari: Ghost Hound	Mystery, Psychological, Sci-Fi, Supernatural	7.59
2199	4879	Mouryou no Hako	Mystery, Seinen, Supernatural, Thriller	7.33